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Published in:
Economic Journal

Publication date:
1994

The Economic Journal, **104** (*March*), 432–443. © Royal Economic Society 1994. Published by Blackwell Publishers, 108 Cowley Road, Oxford OX4 1JF, UK and 238 Main Street, Cambridge MA 02142, USA.

UNEMPLOYMENT DYNAMICS AND DURATION DEPENDENCE IN FRANCE, THE NETHERLANDS AND THE UNITED KINGDOM*

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This paper analyses unemployment dynamics in the French, Dutch and UK labour market. It presents a method to distinguish between the effects of duration dependence and unobserved heterogeneity on the exit rate out of unemployment. It turns out that for British male unemployed there is strong genuine negative duration dependence. For French unemployed there is no strong duration dependence during the first year of unemployment, while for Dutch unemployed there is non-monotonic duration dependence. For all groups of French and Dutch individuals significant unobserved heterogeneity is found. For UK male unemployed, heterogeneity seems to be empirically unimportant.

In the past decade the phenomenon of long term unemployment has puzzled both researchers and policy makers. A central question is whether long term unemployed workers have a low exit rate out of unemployment because of unfavourable personal characteristics or because of stigma effects which reduce the number of job opportunities (see for example Vishwanath (1989) and Van den Berg (1992) for theoretical analyses of the latter).

From a policy point of view the answer to this question is relevant since the policy implications are quite direct. If stigma effects are important then policy should be directed towards preventing workers becoming long term unemployed. If personal characteristics are important, policy may be oriented towards training activities. Furthermore, the degree of state dependence has implications for macro analyses of the labour market (see for example Layard *et al.* (1991)).

It turns out that the answer is difficult to find, precisely because of the fact that the exit rate – or, as it is sometimes called, the hazard rate – out of unemployment decreases over the duration of the unemployment under both hypotheses. In particular, if there is unobserved heterogeneity in the exit rate then the individuals with the largest hazard rate leave unemployment first.

Studies trying to distinguish genuine duration dependence from unobserved heterogeneity basically use micro survey data on unemployment durations. From the end of the 1970s onwards a large quantity of such studies have been carried out (for a survey, see Devine and Kiefer (1991)). They are characterised by strong parametric assumptions on the model specification.

In this paper, we use a method for the nonparametric estimation of all determinants of the unemployment duration distribution (so, including the duration dependence pattern and the distribution of unobserved heterogeneity). This method has been developed by Van den Berg and Van Ours

* We would like to thank Jaap Abbring and Martien Brander for their excellent research assistance. The research of Gerard J. van den Berg has been made possible by a fellowship of the Royal Netherlands Academy of Arts and Sciences.

(1993*a*). It is designed to be applicable to discrete-time time-series data on gross outflows from different unemployment duration classes. Gross (or aggregate, or macro) data have the advantage that they provide the exact values of the exit probabilities (or exit rates) out of the different duration classes considered (averaged over unobserved heterogeneity). The model and the estimation method explicitly take into account that individual exit rates are affected by macro effects like business-cycle effects and seasonal effects. This is another advantage over the usual approach in micro econometric studies on unemployment durations.

We analyse gross data on unemployment durations from France, The Netherlands and the United Kingdom. Developments in unemployment in these countries in the 1980s are quite similar. The average unemployment rate at the beginning of this decade equals about 6–7%. It reached a level of 10–12% in the mid-eighties. In 1990 the unemployment rate in France was 8·9%, in the Netherlands 7·5% and in the United Kingdom 6·8%. (OECD standardised unemployment rates). We use quarterly data which distinguish unemployment by elapsed duration and by gender. All data cover at least a part of the 1980s and the beginning of the 1990s.

The plan of the paper is as follows. Section I presents the model. Basically, this is a Mixed Proportional Hazard (MPH) model in which calendar time replaces the role of the observed explanatory (x) variables. Section II discusses the empirical implementation of the model. The quantities of interest can be estimated from ratios of observed hazards without the need to parameterise the determinants of the hazards. In Section III we describe the data. Section IV presents the results of the analysis. We discuss the parameter estimates and their implications. Furthermore we compare our results to those from previous parametric analyses which attempted to distinguish between duration dependence and unobserved heterogeneity. Section V concludes.

I. MODEL ASSUMPTIONS

In this section we present the unemployment duration model and the underlying assumptions. We use two measures of time, each with a different origin. The variable t denotes the duration of a spell of unemployment for a given individual. The variable τ denotes calendar time. We take t and τ to have the same measurement scale, apart from the difference in origin. Both t and τ are discrete variables. For example, consider an individual who is unemployed for t periods at calendar time τ. If he fails to leave unemployment in period t, he will be unemployed to $t+1$ periods at calendar time $\tau+1$.

For a good understanding of the model and the estimation method, it is useful to have an idea of the type of data for which they are designed to be applicable to. Ideally, gross data give the total numbers of individuals in the labour market who are unemployed for t periods of time ($t = 0, 1, 2, \ldots$) at calendar times τ, $\tau+1$, $\tau+2$, etc. By comparing the number of individuals who are unemployed for t periods of time at τ to the number unemployed for $t+1$

periods at $\tau+1$, we observe the exit rate out of unemployment at calendar time τ for duration t. In other words, we observe the conditional probability that an individual leaves unemployment when being unemployed for t periods, when calendar time equals τ at the moment of exit, for different values of t and τ.

The model aims at explaining variations in unemployment duration distributions in terms of observed and unobserved individual characteristics, calendar time, and the duration dependence pattern. Calendar time is assumed to capture macro effects (including business-cycle and seasonal effects) on individual exit rates out of unemployment. We have separate information for males and females for each of the three countries considered. Therefore, we estimate the model separately for each gender type for each country. In the sequel we present the model for a given gender type and country.

We assume that all variation in the exit rates out of unemployment can be explained by the prevailing unemployment duration t and calendar time τ and by unobserved heterogeneity across individuals. We denote the unobserved heterogeneity variable by v. Consider an individual with unobserved characteristics v who is unemployed for t periods when calendar time equals τ. We denote the conditional probability that this individual leaves unemployment after t periods of unemployment by $\theta(t|\tau, v)$. By definition, this is the exit rate out of unemployment (or hazard rate) at t conditional on τ and v. The unemployment duration density conditional on calendar time and conditional on v can be constructed from these exit rates (see for example Lancaster (1990)).

We make the following assumptions.

Assumptions

1. MPH: $\theta(t|\tau, v)$ has a mixed proportional hazard specification, i.e. there are functions ψ_1 and ψ_2 such that
$$\theta(t|\tau, v) = \psi_1(t)\,\psi_2(\tau)\,v \tag{1}$$
with ψ_1 and ψ_2 positive and uniformly bounded from above. Further, the distribution of v is such that, for every t and τ, $\Pr[0 < \theta(t|\tau, v) < 1] = 1$.
2. Independence of v and τ: v does not depend on the moment of inflow into unemployment and does not change during unemployment.
3. Variation over calendar time: the function ψ_2 is not constant.

The functions ψ_1 and ψ_2 represent the duration dependence and the time dependence of the exit rate out of unemployment. The distribution of v represents the distribution of the unobserved heterogeneity.

Assumptions 1–3 ensure the nonparametric identification of the model. In reduced-form MPH models for micro duration data, dependence on calendar time is usually ignored, and the role of τ in the model above is replaced by the role of observed explanatory variables x. Note that one important difference between the present model and these reduced-form models is that here we have discrete time, whereas in micro studies time is usually treated as continuous. Because of this, we had to introduce the last line of Assumption 1. Note that it imposes the inequality restriction $v < 1/[\psi_1(t)\,\psi_2(\tau)]$ for all v, t, τ. We argue in

Section III that this can be tested. The restriction implies that the support of v is bounded, which in turn implies that all moments of v exist.

II. EMPIRICAL IMPLEMENTATION

In this section we present the strategy to estimate the parameters of interest. Because this strategy has already been discussed rigorously elsewhere (Van den Berg and Van Ours, 1993*a*) the present exposition will be informal.

As mentioned above, the data provide observations on the conditional probabilities that individuals leave unemployment when being unemployed for t periods, when calendar time equals τ at the moment of exit, for different values of t and τ. These probabilities are unconditional on the unobserved heterogeneity term v, and will be denoted by $\theta(t|\tau)$. To express them in terms of the exit rates $\theta(t|\tau, v)$, we have to integrate v out of the latter. We get

$$\theta(t|\tau) = \frac{\psi_1(t)\,\psi_2(\tau)\,\mathrm{E}_v\left\{v\prod_{i=1}^{t}[1-\psi_1(t-i)\,\psi_2(\tau-i)\,v]\right\}}{\mathrm{E}_v\left\{\prod_{i=1}^{t}[1-\psi_1(t-i)\,\psi_2(\tau-i)\,v]\right\}} \tag{2}$$

in which we use the convention that the product term is one if $t = 0$.

Denote $\mathrm{E}_v(v^i)$ by μ_i. By expanding the product terms in (2) we get the following result: $\theta(t|\tau)$ depends on $\{\psi_1(i), \psi_2(\tau-t+i), \mu_{i+1}, \text{with } i = 0, 1, \ldots, t\}$. We will call the elements of the latter set the 'parameters', even though they really are values of functions on $\mathbb{N}$ and summary statistics of the underlying heterogeneity distribution, respectively.

Typical samples contain information on $\theta(t|\tau)$ for a small number n_t of different durations and a large number n_τ of different points of time. In such cases, the number of parameters is large relative to the number of observations. In particular, for each $\psi_2(\tau)$ parameter the number of observations that contain information on that parameter is extremely small, so the estimate of it would be unreliable. However, note that we are primarily interested in estimating the duration dependence and unobserved heterogeneity parameters and that the calendar time dependence parameters are nuisance parameters. Van den Berg and Van Ours (1993*a*) present a strategy for estimating the parameters of interest only. Basically, these ideas amount to substituting values of past observed exit rates into the expressions (2) for $\theta(t|\tau)$, and examining ratios of the resulting expressions for different t.

As an example, consider $\theta(1|\tau)$. From (2), it follows that this is equal to $\psi_1(1)\,\psi_2(\tau)\,[\mu_1-\psi_1(0)\,\psi_2(\tau-1)\,\mu_2]/[1-\psi_1(0)\,\psi_2(\tau-1)\,\mu_1]$. But from (2) it also follows that $\psi_1(0)\,\psi_2(\tau-1)$ equals $\theta(0|\tau-1)/\mu_1$. Consequently,

$$\frac{\theta(1|\tau)}{\theta(0|\tau)} = \frac{\psi_1(1)}{\psi_1(0)}\,\frac{1-\theta(0|\tau-1)\,\mu_2/\mu_1^2}{1-\theta(0|\tau-1)} \tag{3}$$

in which ψ_2 does not show up anymore. Denote μ_i/μ_1^i by γ_i $(i \geqslant 2)$, and $\psi_1(t)/\psi_1(t-1)$ by η_t $(t \geqslant 1)$. The parameters η_t represent the duration dependence of the exit rate as a function of t, whereas the parameters γ_i represent the normalised moments of the distribution of unobserved heterogeneity. The general result is

$$\frac{\theta(t\,|\,\tau)}{\theta(t-1\,|\,\tau)} = \eta_t\{\text{expression depending on } \theta(i-1\,|\,\tau-t+i-1) \text{ and } \gamma_{i+1} \text{ with } i = 1, 2, \dots, t, \text{ and, if } t \geqslant 2, \text{ on } \theta(i-1\,|\,\tau-t+i) \text{ with } i = 1, 2, \dots, t-1\}. \tag{4}$$

As a second example, for $t = 2$ we get

$$\frac{\theta(2\,|\,\tau)}{\theta(1\,|\,\tau)} = \eta_2 \frac{1-\theta(0\,|\,\tau-1)}{[1-\theta(1\,|\,\tau-1)]\,[1-\theta(0\,|\,\tau-2)]} \times \frac{1-\gamma_2\,\theta(0\,|\,\tau-2)-\theta(1\,|\,\tau-1)\,[1-\theta(0\,|\,\tau-2)]\dfrac{\gamma_2-\gamma_3\,\theta(0\,|\,\tau-2)}{1-\gamma_2\,\theta(0\,|\,\tau-2)}}{1-\gamma_2\,\theta(0\,|\,\tau-1)}. \tag{5}$$

Such ratios of observed exit rates can be used to estimate the parameters of interest. For each parameter η_t and γ_i, the number of observations that contain information on it is relatively large. If we observe exit rates for durations $\{0, 1, \dots, n_t-1\}$ and calendar times $\{T+1, \dots, T+n_\tau\}$ then the number of parameters in the expression for $\theta(t\,|\,\tau)/\theta(t-1\,|\,\tau)$ equals $(2n_t-1)$.

To estimate the parameters of ψ_2, an analogous procedure can be proposed, based on expressions for the ratios $\theta(t\,|\,\tau)/\theta(t\,|\,\tau-1)$. However, as noted above, the number of duration classes n_t would have to be quite large to get reliable estimates. Moreover, as t increases, the expressions for $\theta(t\,|\,\tau)$ become increasingly cumbersome.

Let us return to the ratio $\theta(t\,|\,\tau)/\theta(t-1\,|\,\tau)$. If there is no unobserved heterogeneity, then $\theta(t\,|\,\tau)/\theta(t-1\,|\,\tau) = \eta_t$, which does not depend on τ. (This can be checked by noting that in that case $\mu_i = \mu_1^i$ for every $i \geqslant 1$, so $\gamma_i = 1$.) If there is unobserved heterogeneity, then in general these ratios do depend on τ. For example, $\theta(1\,|\,\tau)/\theta(0\,|\,\tau)$ depends on $\theta(0\,|\,\tau-1)$ if and only if $\gamma_2 \neq 1$, which in turn holds if and only if there is unobserved heterogeneity. The exit rate $\theta(0\,|\,\tau-1)$ varies with τ by virtue of Assumption 3, so, in sum, $\theta(1\,|\,\tau)/\theta(0\,|\,\tau)$ varies with τ if and only if there is unobserved heterogeneity. This means that the parameters associated with the distribution of unobserved heterogeneity are identified from cross effects of t and τ in $\log \theta(t\,|\,\tau)$.

Clearly, the MPH assumption is crucial. Van den Berg and Van Ours (1993*a*) provide a number of specification tests. Consider for example the estimates of $\gamma_2, \dots, \gamma_{n_t}$. If the model is correct, then $\gamma_2, \dots, \gamma_{n_t}$ are mutually consistent as normalised moments of a distribution with positive bounded support (from zero until the upper bound depending on the functions ψ_1 and ψ_2). This can be tested for. For example, if $\gamma_2 < 1$ or $\gamma_3 < \gamma_2^2$ then there is no distribution with positive support that is able to generate such moments (see Shohat and Tamarkin (1970); for example $\gamma_2 < 1$ would imply $\mathrm{Var}(v) < 0$). If these necessary conditions are not violated, then one can usually find a discrete distribution that is able to generate the γ_i estimates (see Shohat and Tamarkin

(1970) and Lindsay (1989)). It should be noted that in general there will also be non-discrete distributions that are able to generate a given finite set of moments. Consequently, if the estimated γ_i are normalised moments of some distribution, then in general there will be more than one distribution function $G(v)$ consistent with them. It can be shown that these moment tests are informative on the validity of Assumption 1. Also, they may detect misspecification of the unit of time period.

Before finishing this section we discuss the incorporation of seasonal effects into the model. We distinguish two types of seasonal effects on the exit rate. First, there may be an effect that affects every individual in a similar way. For example, there may be less activity on the labour market during the holiday season. This effect is captured by the $\psi_2(\tau)$ terms in the model. Secondly, there may be an effect that only affects the individuals in the inflow into unemployment. For example, the average success of individuals in the inflow at the end of the schooling season may be different than that at other times of the year. To incorporate this, we allow for dependence of $G(v)$ on the moment of inflow, so we relax Assumption 2. We assume that the season affects a scale parameter of the distribution $G(v)$. For example, for two seasons A and B, we assume that $G_B(v) = G_A(\omega v)$. If $\omega > 1$ then A is a 'better' season than B. In this model, the normalised moments of v do not depend on the season in which inflow occurs.

It can be shown that the only thing that changes in (4) is that the r.h.s. has to be multiplied by the scale parameter giving the change in $G(v)$ when going from the season at $\tau - t$ to the season at $\tau - t + 1$. For example, if $\tau - t$ is a season of type A and $\tau - t + 1$ is a season of type B and $G_B(v) = G_A(\omega v)$, then $\theta(t \mid \tau)/\theta(t-1 \mid \tau)$ is equal to a factor ω times the expression in the r.h.s. of (4). Thus, the seasonal effects are estimated along with the other parameters.

In the application, the duration of a season is taken to equal the unit of time, which is one quarter. Thus, we have four seasons and four additional parameters ω_1, ω_2, ω_3 and ω_4 defined by $G_1(v) = G_4(\omega_1 v)$ and $G_i(v) = G_{i-1}(\omega_i v)$ for $i \in \{2, 3, 4\}$, with $\omega_4 = 1/(\omega_1 \omega_2 \omega_3)$. So, if $\omega_i < 1$ then the average success of the newly unemployed workers in season i is larger than in the inflow one quarter earlier.

It should be noted that possible business-cycle effects on the composition of the inflow into unemployment can be modelled in the same way. The cycle can be divided into a number of phases, and the phase can be assumed to affect a scale parameter of $G(v)$. Below we use diagnostic checks to examine whether such effects are present. A more extensive application is left to future research.

III. DATA

For the model to be applicable, the frequency at which the data are collected has to equal one over the size of the unemployment duration classes (i.e. the unit time period in the model). We use quarterly data for France, The Netherlands and the United Kingdom. (We also tried to find adequate data for other European countries, but the data were either prohibitively expensive or simply not available.)

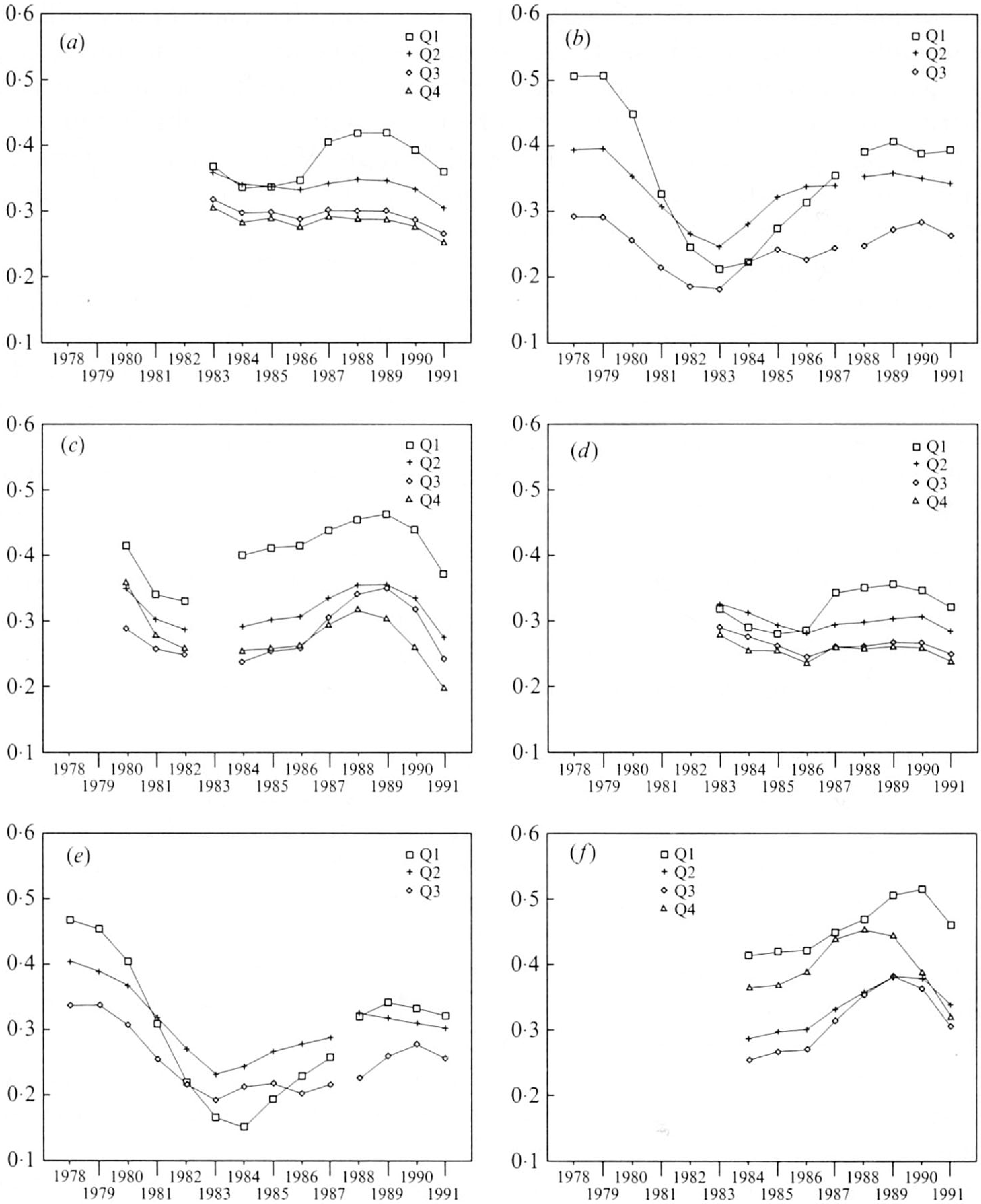

Fig. 1 (*a–f*). Quarterly exit rates out of unemployment (yearly averages) for (*a*) France, (*b*) The Netherlands, (*c*) United Kingdom – Males. Quarterly exit rates out of unemployment (yearly averages) for (*d*) France, (*e*) The Netherlands, (*f*) United Kingdom – Females.

The French data are on the period 1982.1–92.1 and are collected by the French public employment offices. Figs. 1*a* and 1*d* show the exit rates – averaged over the year – for the first four quarters of unemployment.

The data for The Netherlands cover the period 1978.1–91.4 and are also collected by the public employment offices. However, the data are not collected in a single way over this whole period. In the subperiod 1978.1–87.4 the data refer to all job seekers registered at the unemployment office. In the subperiod 1988.1–91.4 the data refer to unemployed registered job seekers. A substantial part of all registered job seekers is unemployed (in the period involved about 80 %). Nevertheless, we account for the change in data collection. We assume that the effect on the number of unemployed in each duration class caused by the change in data collection is multiplicative. Then, by deleting those observations on ratios of exit rates which would result in model equations containing exit rates from both subperiods, we estimate our model using data from both subperiods (see Van den Berg and Van Ours (1993*b*) for details).

For the first subperiod (1978.1–87.4) there is no information on exit rates for the fourth quarter of unemployment. Therefore we restrict ourselves to data on exit rates for the first three quarters of unemployment. This means that we only use two equations of the form (4), namely one for $\theta(1\,|\,\tau)/\theta(0\,|\,\tau)$ and one for $\theta(2\,|\,\tau)/\theta(1\,|\,\tau)$. For France and the United Kingdom we use also data on $\theta(3\,|\,\tau)$, so we have one additional equation.

Figs. 1*b* and 1*e* show the – yearly averages of the – exit rates for The Netherlands. There are obviously more fluctuations than in the French exit rates. This is partly due to the incorporation of the period 1980–3 in which the recession led to a sharp decrease in all exit rates. The exit rate for the first quarter of unemployment was about 0·5 in 1980, while it was about 0·17 in 1983.

In the British unemployment data there are also discontinuities. A major change is the one in October 1982, when the counting of those registered at public employment offices as being unemployed was replaced by the counting of benefits claimants as being unemployed. For both male and female unemployed workers we use data on the period 1983.4–92.2 in which benefits claimants were counted as unemployed. In addition, we use the information published in Haskel and Jackman (1988) on male unemployed for the period 1979.2–83.3. Those data have been constructed by a procedure described in Haskel (1988) which transforms the original data into a consistent time series based on the February 1986 United Kingdom definition of unemployment. Although in theory the male unemployment data are consistent over the period 1979.2–92.2 we allowed for differences before and after 1983.4 in the same way as for the Dutch series.

Haskel and Jackman (1988) do not present – or use – information on female unemployment because they consider the official unemployment statistics to be a poor measure of the actual female unemployment rates. Whereas 90 % of the unemployed men claim benefits, less than half of the unemployed women are benefit claimants. An additional reason to exclude women from their dataset is that, whereas most male unemployed exhaust their entitlement to unemployment benefits after a year and become eligible instead for supplementary benefits, most married women are not eligible for supplementary benefits. So, generally married women officially leave unemployment after one year without actually finding a job.

Figs. 1*c* and 1*f* show the – yearly average of the – exit rates for the first four quarters of unemployment. The exit rates for male unemployed display over a large part of the calendar period the familiar ranking from high to low exit rates as the duration of unemployment increases. For French and Dutch females, the pattern in the decrease of the exit rate over the duration is similar to that for males. This is not true for British females. A peculiar phenomenon is the high exit rate for the fourth duration quarter, which may have to do with the phenomenon described at the end of the previous paragraph.

IV. RESULTS

For France and the United Kingdom we use the exit rates for the first four quarters of unemployment. Following Section III we specify 3 equations, as follows: $\log \theta(t \mid \tau)/\theta(t-1 \mid \tau)$ equals the log of the corresponding expression on the r.h.s. of (4), plus an error term (so each $t \in \{1, 2, 3\}$ defines one equation). The error terms represent specification errors that are identically distributed over equations and over observations. We assume that the errors in a given equation are independent across the observations. On the other hand, we allow the errors in different equations to be contemporaneously related. So, at a given point of calendar time, the specification errors for different ratios of exit rates may be related. We do not make a parametric assumption on the distribution of the error terms.

The 3 equations contain 3 heterogeneity parameters $(\gamma_2, \gamma_3, \gamma_4)$, 3 duration dependence parameters (η_1, η_2, η_3) and 3 seasonal-effect parameters ω_1, ω_2 and ω_3 (note that ω_4 follows from these). We estimate the parameters using Seemingly Unrelated Nonlinear Regression.

For The Netherlands our information is limited to 3 duration classes and we estimate 2 equations over the period 1978.1–91.4.

The estimation results are shown in Table 1. For France and The Netherlands the γ_i estimates imply that there is significant unobserved heterogeneity for both males and females. Neither of the specification tests mentioned in Section III is rejected. Using results in Shohat and Tamarkin (1970) it can be inferred from the γ_i estimates that for each subgroup $G(v)$ can be approximated well by a discrete distribution with two positive point of support.

There does not seem to be much duration dependence in the first four quarters of unemployment duration in France. The average exit rate over the first year, corrected for unobserved heterogeneity, is slightly decreasing for both male and female workers.

The duration dependence pattern for unemployment duration in The Netherlands is non-monotonous: there is an increase when going from the first to the second quarter and a decrease when going from the second to the third quarter. The net effect over the first nine months of unemployment is slightly positive. Note that the differences between the results for France and The Netherlands are much larger than the differences between results for males and females within each country. Also note that there are significant effects of the season at the moment of inflow into unemployment on the exit rate out of unemployment.

To examine the fit of the model more closely we carried out a number of diagnostic checks based on the residuals of the estimated equations. It turns out that for France the fit is very good. However, the model cannot explain the fact

Table 1

Non-parametric Estimation Results; France, The Netherlands and the United Kingdom

(Standard errors in parentheses)

	France		The Netherlands	
	Males	Females	Males	Females
γ_2	1·21 (0·04)	1·22 (0·06)	1·34 (0·03)	1·37 (0·04)
γ_3	1·74 (0·14)	1·90 (0·25)	2·13 (0·08)	2·37 (0·14)
γ_4	2·86 (0·40)	3·77 (0·83)		
η_1	1·03 (0·03)	1·04 (0·04)	1·23 (0·03)	1·33 (0·04)
η_2	0·94 (0·02)	0·93 (0·03)	0·89 (0·03)	0·95 (0·03)
η_3	1·00 (0·02)	1·01 (0·03)		
ω_1	1·09 (0·01)	1·09 (0·01)	0·80 (0·02)	1·02 (0·02)
ω_2	1·01 (0·01)	0·98 (0·01)	1·23 (0·02)	1·01 (0·02)
ω_3	0·91 (0·01)	0·93 (0·01)	0·90 (0·02)	0·93 (0·02)
ω_4	1·00 (0·01)	1·01 (0·01)	1·13 (0·02)	1·04 (0·02)

	United Kingdom	
	Males	Females
γ_2	1·04 (0·04)	0·91 (0·04)
γ_3	1·17 (0·15)	0·83 (0·15)
γ_4	1·03 (0·58)	2·58 (0·51)
η_1	0·80 (0·03)	0·68 (0·02)
η_2	0·88 (0·02)	0·87 (0·02)
η_3	0·91 (0·03)	1·53 (0·05)
ω_1	0·94 (0·01)	0·97 (0·01)
ω_2	1·08 (0·01)	1·09 (0·01)
ω_3	0·97 (0·01)	0·97 (0·01)
ω_4	1·02 (0·01)	0·98 (0·01)

the size of $\theta(0|\tau)$ relative to the other exit rates is smaller before 1986 than it is after 1986 (see Fig. 1). For The Netherlands the fit of the first equation is much better than the fit of the second equation.

For British males we do not find significant heterogeneity, since none of the γ_i estimates differs significantly from one. The specification tests do not result in rejections. For British females the γ_2 estimate is significantly smaller than one. Thus, the model specification is rejected. This is probably a consequence of the fact that the data are unreliable due to the criteria by which British females are considered to be unemployed.

For British male unemployed workers there is strong negative duration dependence. Corrected for heterogeneity, the exit rate for the second quarter is 80% of that for the first quarter and the exit rate for the third quarter is 88% of that for the second quarter.

The estimated residuals for British males show that for $\theta(0|\tau)$ the discontinuity in the data gathering procedure in 1983 is not accommodated, despite the corrections made in Section III (see also Fig. 1*c*). However, using only data from the period after 1983 does not alter the main results. The United Kingdom estimated residuals suggest that business-cycle effects on the composition of the inflow into unemployment may be present. For the period 1987–90 the duration dependence of the observed exit rates seems to be less negative than as predicted by the model, while for the other periods the reverse seems to hold.

It may be interesting to compare our empirical results on the presence of duration dependence and unobserved heterogeneity to those in other empirical studies on unemployment durations based on MPH models. There is a large number of studies that use data from Britain or The Netherlands and that are based on parameterised MPH models (see for example Lancaster (1979), Narendranathan *et al.* (1985), Lynch (1985), Kooreman and Ridder (1983), Van Opstal and Theeuwes (1986), and Van den Berg *et al.* (1991)). The results are ambiguous, dependent on the particular parametric specification for the duration dependence pattern and the heterogeneity distribution, and sometimes not very plausible.

Kerckhoffs *et al.* (1991) take a flexible (piecewise constant) specification for the duration dependence and a discrete distribution for v and estimate the model separately for Dutch males and females, allowing the exit rates to depend on observed explanatory variables x. The authors conclude that for males as well as females there is strong evidence for non-monotonic duration dependence (namely, first increasing and then decreasing). This finding is supported by our results. Note that generally empirical studies take parametric monotonous (Weibull) specifications for duration dependence.

Jackman and Layard (1991) use British data that are similar to ours. They construct nonparametric 'eyeball' tests that compare data from different steady states in the sample period. They find evidence for strong negative duration dependence. The evidence for the presence of unobserved heterogeneity is rather weak. These results are in accordance to our results on British men. In sum, our results on duration dependence confirm previously found results that are based on flexible specifications.

V. CONCLUSION

In this paper we analyse unemployment dynamics in the French, the Dutch and the British labour markets. In particular, we non-parametrically distinguish between unobserved heterogeneity and duration dependence in unemployment durations, using aggregate time series data on male and female exit rates out of unemployment.

For British male individuals we found strong genuine negative duration dependence, i.e. a decline of the exit rate over duration for a given individual. For French individuals there is no strong duration dependence during the first year, while for Dutch individuals there is non-monotonous (inverse-U shaped) duration dependence over the first three quarters of unemployment. For British females the model specification tests resulted in rejection, which is probably due to the low quality of the data for this group.

For all groups of French and Dutch individuals considered, we found significant unobserved heterogeneity in the unemployment duration distribution. For British males, heterogeneity seems to be empirically unimportant. Finally, there are significant effects of the season at the moment of inflow into unemployment on the exit rate out of unemployment.

Several topics for future research emerge. First, it seems worthwhile to use more observable information on heterogeneity of unemployed individuals, for example by distinguishing by both gender and age group. Furthermore, information on cyclical developments in the labour market may be used to estimate the way in which exit rates depend on calendar time. The results can then be compared to various macro time series data.

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